Synopsis

An Efficient Approach for Partial Fingerprint Recognition Based on Pores and SIFT Features using Fusion Methods

Submitted

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SYNOPSIS

1. INTRODUCTION

Reliable authentication of people has long been an interesting goal and is becoming more important as the need of security grows. Security is an aspect that is given top priority by organizations, educational institutions, political and government in personal identity and forgery issues. Technologies called biometrics can automate the identification of people by one or more of their distinct physical or behavioral characteristics. They are pattern recognition system which makes personal identification by determining the authenticity of the specific characteristic possessed by the user.

Biometrics has come to occupy an increasingly important role in human identification primarily to their universality and uniqueness (Cuntoor *et al*., 2003). As a result of this evolution, a new breed of techniques and methods for user identity recognition and verification has appeared based on the biometric features that are unique to each individual. Examples of common biometrics used include iris, DNA, voice patterns, facial patterns and fingerprint (Jain *et al*., 2004). Among these fingerprint is more popular biometric modality and has been used for personal identification for more than 100 years. The popularity is due to the fact that fingerprints never change and no two fingerprints are similar (Pankanti, *et al*., 2002). It has been proven that even identical twins have different fingerprints.

Because of these desirable properties, automated systems for Automatic Fingerprint Recognition System (AFS) have been developed and over the years this interest has increased steadily. Several researchers have probed on using the intricacies of the fingerprint to create a robust and accurate AFS. The AFS combine image processing algorithms with fingerprint impression and map a fingerprint to an individual from a fingerprint database.

Currently, there are three types of AFS, namely, minutiae-based, correlation-based, and image-based. In minutiae-based approaches, minutiae (i.e. endings and bifurcations of fingerprint ridges) are extracted and matched to measure the similarity between fingerprints. The correlation-based methods spatially correlate two fingerprint images to compute the similarity between them, while the image-based methods first generate a feature vector from each fingerprint image and then compute their similarity based on the feature vectors.

Although fingerprint matching based on minutiae features is a well researched problem in the field of AFS (Ratha and Bolle, 2004; Maltoni *et al.*, 2003), it is still an unsolved problem presenting many research challenges. Most of the existing solution algorithms assume that the two templates are approximately of the same size. This assumption is no longer valid. The need for recognition of partial fingerprint has increasing in both forensic and civilian applications. In forensics, latent fingerprints lifted from crime scenes are often noisy and broken, thus the usable portions are small and partial. In civilian applications, the invention of small hand-held devices, such as mobile phones, PDAs, and miniaturized fingerprint sensors present considerable demands on partial fingerprints processing. Matching partial fingerprints against full pre-enrolled images in the database presents several problems (Jea and Govindaraju, 2005)

(i) the number of minutiae points available in such partial fingerprints are few, thus reducing its discriminating power.
(ii) loss of singular points (core and delta) is likely and therefore, a robust algorithm independent of these singularities is required.
(iii) difficult to ascertain correspondence of partial fingerprint even if ten-prints are available.
(iv) uncontrolled impression environments result in unspecified orientations of partial fingerprints.
(v) the skin elasticity and humidity can cause distortions, which increase the ambiguity between genuine and imposter samples.

Generally, a fingerprint based biometrics system is considered as highly secure and is equivalent to a long password system. However, with the decreasing number of features on a small fingerprint and the non-exact matching nature, the security strength of partial fingerprint recognition reduces. The most desirable properties of high accuracy, low error rate and maximum speed is yet to be achieved with Automatic Partial Fingerprint Recognition System (APFS).

In order to further improve the accuracy of APFS, people are now exploring more features apart from minutiae on fingerprints. The recently developed high resolution fingerprint scanners make it possible to reliably extract level3 features such as pores. Pores have been used as useful supplementary features for a long time in forensic applications (Zhao *et al.*, 2010). Using pores in APFS has two distinct advantages. (i) Pores are more difficult to be damaged or mimicked than minutiae and (ii) Pores are abundant on fingerprints (Parthasaradhi *et al.*, 2005)

Even a small fingerprint fragment could have a number of pores. The density of pores on a ridge varies from 23 to 45 pores per inch and it has been proved that a minimum of 20 to 40 pores is enough to determine the identity of person (Ashbaugh 1999). Therefore, pores are particularly useful in partial fingerprint recognition where the number of minutiae is very limited.

In this dissertation, the main objective is to design a partial fingerprint recognition system based on non-minutiae features which would operate efficiently on the extremes of all three axis simultaneously (high accuracy, high scalability and easy to implement and use). To achieve this primary goal, the study proposes an APFS with four components.

1. **Preprocessing Module –** contains procedures for improving the quality of the fingerprint image through automatic brightness, contrast, color level adjustment and noise removal.
2. **Segmentation Module –** To extract the region of interest (fingerprint) from the background using corner detection algorithms.
3. **Feature extraction Module –** To extract the non-minutiae features from the fingerprint Two types of features are considered
    a. Local Binary Patterns (LBP) around Pore Feature
    b. Scale Invariant Feature Transformation (SIFT) Feature
4. **Matching Module –** To match the extracted features with a full-fingerprint database to identify a person. Two types of matching algorithms are used.
    a. Score based matching
    b. Neural Network based matching

2. METHODOLOGY

The proposed APFS consists of three major steps which are Acquisition (Sensors and data storage components), Recognition and Decision process. A fingerprint sensor is used to collect fingerprints, which are converted to a digital format and are stored as template. The template is used during decision process where input fingerprint is compared with the template. After acquisition, an input partial fingerprint is presented and a search with template fingerprints is performed (one-to-many matching). The anticipated result of search is a match or non-match. Using this result, a decision process uses this result to make a system level decision. The research design of the proposed APFS is given in Figure 1 and each of the phases is explained in this section.

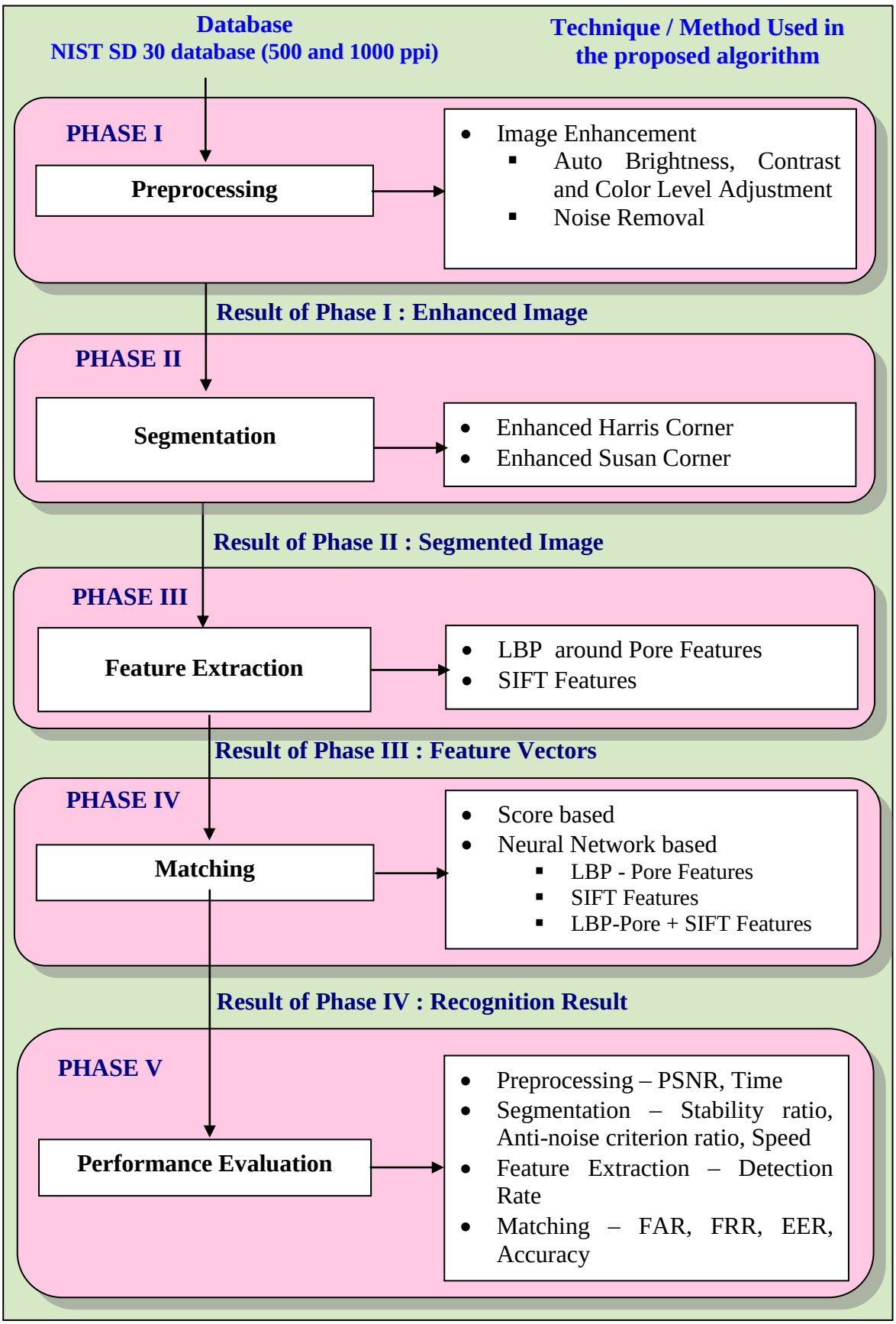

Figure 1 : Research Methodology

2.1. Preprocessing

Preprocessing consist of routines that improves the quality of a fingerprint image. This phase focus on four main aspects of image quality, namely, Auto Brightness Adjustment, Auto Contrast Adjustment, Auto Colour Level Adjustment and Image Denoising. Fingerprint images normally acquire impulse noise (Salt & Pepper, Random).

The algorithm performs image enhancement in two steps. The first step performs a simultaneous operation to adjust brightness, contrast and color levels. In this procedure, the image is first converted to a YUV colour space. The luminance is used for adjusting brightness and contrast, while the Q component is used for color level adjustment. After adjustment, a RGB colour space conversion is performed. In the second step, an enhanced Vector Median Filter (VMF) is used to remove the impulse noise. The enhanced version of VMF has the advantage of edge preservation and reduction of computation complexity.

2.2. Segmentation

The main aim of this phase is to identify the fingerprint area by splitting fingerprint into two regions, namely, Foreground and Background. The foreground will have the fingerprint is the Region Of Interest (ROI) and the unwanted background can be removed from further analysis. The advantage of this phase is that since the unwanted regions are removed, the computations are performed only on ROI and thus saves processing time and cost.

Two most frequently used approaches for segmentation are pixel-based and edge-based. Out of the two, edge-based techniques are more frequently used. Traditional edge-based algorithms efficiently identify edges, but work poorly with corners. The present research work focuses on two corner-based segmentation algorithms, namely, Harris Corner and Susan Corner detection algorithms. The disadvantages of Harris and Susan are the computing derivative is sensitive to noise, they generate “false” corners and has poor localization performance because it needs to smoothen the derivatives for noise reduction.

All these problems are solved by finding the edges of the image and then perform Harris or Susan only on the detected edges alone. This saves time and avoids false detection and is not noise sensitive. The present research work analyzes the performance of the various traditional edge detection algorithms (Canny, Sobel, Roberts, LoG and Prewitt) and selects the best. Experiments show that Canny is efficient and it is used. This phase thus proposed two corner

detection algorithms to segment fingerprint from its background. The first is the Enhanced Harris Corner-based segmentation and the second is the Enhanced Susan Corner-based segmentation algorithms.

2.3. Feature Extraction

In this phase, it extracts two types of features. They are LBP features around pores and SIFT features. The process of extracting LBP-based on pores involves the following steps. Initially, an extractor that uses a Marker-controlled watershed Segmentation method is used to extract the pores of the fingerprint. The second step considers each pore and constructs eight LBP histograms for each pixel around the pore. These are concatenated and used as features for the fingerprint.

The SIFT feature extraction algorithm consists of the following steps. The first step constructs image octaves and DoG (Difference of Gaussian) images. The second step identifies stable local extrema points by searching for stable features in the DoG space across different scales. The third step (repeated for each feature point), obtains a descriptor by using the histogram of gradient orientation around the corresponding local extremum (4x4 array of histograms with 8 different orientation bins in each). The generated descriptor contains texture information for each feature point. The advantages of SIFT features are two-fold. The first is that the identified features are invariant to scale, rotation and affine transformations and the second, they are robust and efficient in image matching.

2.4. Matching Process

Two matching algorithms are used during the identification process of the partial fingerprint with the full fingerprint template. The procedures are explained below.

1. The first one is based on **Single-feature based score-level matching**. In this method, the matching algorithm compares a single feature (LBP- Pore feature vector or SIFT feature vector) against the template and uses a threshold to find a successful identification of a fingerprint.
2. The second method uses a **Multiple-feature based score-level fusion matching.** Here the two features based matching scores are combined using a weighted sum rule method. The cumulative matches are calculated and the matching score between two images is decided

based on the number of matching points. A decision threshold is used during the decision making process.

3. The third matching technique uses a **neural network based classification with single feature vector** (LBP-Pore feature vector or SIFT feature vector) for declaring a partial fingerprint as either a match or non-match. A trained Back Propagation neural network is used during the decision making.
4. The fourth matching technique proposes the use of a **feature fusion framework with neural network classification**. The fusion framework unifies LBP- Pore feature and SIFT feature for classification. The two feature vectors are fused using a multi-algorithmic fusion method, where two different feature vectors extracted from the same image are fused to form a single high dimensional feature vector. Using the fused feature vector, a back propagation neural network classifies an input image into the two selected categories.

3. EXPERIMENTAL RESULTS

All the experiments were conducted using National Institute of Standard and Technology Special Database 30 (NIST SD30) dual resolution (500 and 1000ppi) database containing 36 ten-print paired cards. Two sets of fingerprints for one individual captured at different session. Partial fingerprint images are randomly generated with various sizes such as 10%, 20%, 30%, 40%, 50% and 60%. A 60-40 division method was used to create the training and testing set.

Four stages of experiments were conducted to evaluate the various stages of the proposed APFS. The **first stage** experiment evaluates the **preprocessing algorithms** using two metrics, namely, Peak Signal to Noise Ratio (PSNR) and speed of preprocessing. Two types of impulse noises, namely, random and salt & pepper noise were considered and the performance of noise removal with both these types were examined. The results are compared with the traditional filters median and VMF algorithms. The results proved that the Enhanced Vector Median Filter algorithm is best suited for removing the impulse noise of the fingerprint image and it is an improved version of the traditional VMF algorithm.

The **second stage** evaluates the **segmentation algorithms,** Enhanced Harris Corner and Enhanced Susan Corner detection algorithms, using stability ratio, anti-noise ratio and segmentation speed. The enhanced versions were compared with the traditional Harris corner-based and Susan corner-based segmentation algorithms. The results proved that while both the enhanced method is better than their traditional counterparts, the enhanced Harris corner algorithm is best suited for segmenting fingerprint region from its background.

The accuracy of **pore detection** is analyzed in the **third stage** of experimentation. The metric True Detection Rate (R_T) and False Detection Rate (R_F) are used for the number of pores detected. The results are compared with four existing methods Ray's Method (Ray *et al.*, 2005), Jain's Method (Jain *et al.*, 2007), Adaptive DoG Based Method (Parsons *et al.*, 2008) and Adaptive Pore Model Method (Zhao *et al.*, 2008). The results proved that the Marker Controlled watershed Segmentation method is best suited for extracting the pore features which was evident from the high true detection rate and low false detection rate obtained. This proves that the proposed method can detect pores on fingerprint images more accurately.

The **fourth stage** of experiments were conducted to evaluate the performance of the **six matching algorithms**, LBP-Pore features with score-level matching, SIFT features with score-level matching, LBP-Pore and SIFT features score-level fusion matching, LBP-Pore features with neural networks, SIFT features with neural networks and Fused LBP-Pore and SIFT features with neural networks. The six models were analyzed using the performance metrics namely, False Acceptance Rate, False Rejection Rate, Equal Error Rate, Total Error Rate, and Overall Accuracy. Experiments were also performed to analyze the effect of preprocessing and segmentation on fingerprint recognition accuracy. Figure 2 shows the overall average accuracy obtained by the score-based and neural network-based matching with LBP-Pore features, SIFT features and fused features for the selected partial fingerprints.

4. FINDINGS OF THE STUDY

Preprocessing and segmentation improved the recognition accuracy. The inclusion of preprocessing with score based fusion algorithm showed an efficiency gain of 1.55%, while the inclusion with fusion neural network showed 3.01% an efficiency gain with respect to recognition accuracy. The inclusion of segmentation algorithm increased the accuracy efficiency of the fused models by 2.56% and 4.16% with score level fusion and neural network fusion algorithm when compared with the single feature algorithm.

Comparing single feature and multiple feature algorithms LBP-Pore and SIFT achieved accuracy gain of 11.12% efficiency over SIFT and 0.84% over LBP-Pore while using score level matching algorithm and 8.97% efficiency over SIFT, 1.28% efficiency over LBP-Pore while using Neural Network based matching process. Comparing score-based and neural networks, neural networks produced improved accuracy by 1.54% in terms of Accuracy.

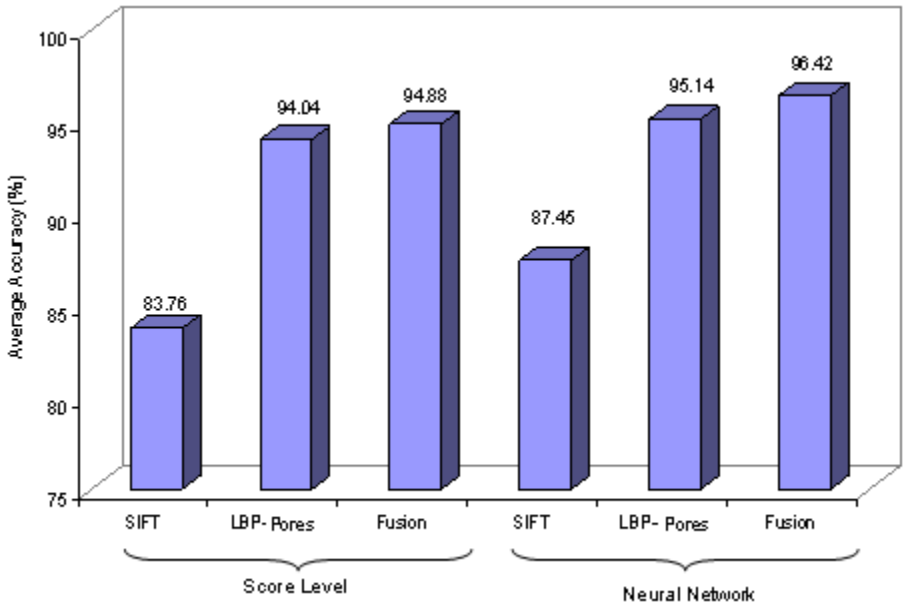

Figure 2 : Average Accuracy

The results further showed that the partial fingerprint size and Efficiency of the proposed models are directly proportional. The proposed system produced maximum of 98.14% accuracy when 60% of image size was used as input to APFS. The low FAR and FRR values shows that the Forgery fingerprints are correctly identified and Genuine fingerprints are hardly rejected. The low EER values of both score based and neural network based algorithms (4.71% and 2.55% respectively) shows that the fusion based algorithm identifies genuine and forgery fingerprints in an efficient manner. In all cases, the pore based algorithm performed better than SIFT based algorithm and combining pore and SIFT features for recognition, increased accuracy and decreased error rate.

5. CONCLUSION

From the various results it could be understood that the proposed algorithm achieve high recognition rate even with a small partial fingerprint and can be considered as advanced solutions by high security applications. The proposed algorithm is faster and reduces process overheads when compared with traditional minutiae based algorithms as it avoids tasks like feature alignment and orientation. The proposed models with both single and fused features combined with score level and neural network matching algorithms are comparable with the standard quality required for the recent security and authentication applications. The use of LBP-Pore features combined with SIFT features for fingerprint recognition produces high accuracy and reduced errors.

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